REMARKS

I. Claim Objections

Claim 10 was objected to under 37 CFR I.75(c), as being of improper dependent form for failing to further limit the subject matter of a previous claim. The Examiner argued that the Applicant is required to cancel the claim(s), or amend the claim(s) to place the claim(s) in proper dependent form, or rewrite the claim(s) in independent form. The Examiner asserted that the disclosed molecular connections are inherently required to comprise molecules as is everything else that is physical.

The Applicant has amended claim 10 to refer to nanoconductors. Thus, the objection to claim 10 has been traversed. The Applicant respectfully requests withdrawal of the objection to claim 10.

Claim 19 was objected to because of the following informalities: Claim 19 depends on itself and is thus in improper dependent claim form (see 37. C.F.R.§1.67). The Examiner asserted that this claim was intended to depend from claim 18, and has been treated as such for the remainder of this office action, however appropriate correction is required.

The Applicant has amended claim 19 so that claim 19 is dependent upon claim 18. Thus, the objection to claim 19 has been traversed. The Applicant respectfully requests withdrawal of the objection to claim 19.

II. Claim Rejections 35 U.S.C. § 112

The Examiner rejected claim 11, arguing that claim 11 recites the limitation "molecular nanoconnections" in line 3. The Examiner asserted that there is insufficient antecedent basis for this limitation in the claim, and that the only type of connections in this claim's depending claim tree have only been described simply as "molecular."

The Applicant has amended claim 11 so that the reference to "molecular" has been removed. The Applicant therefore submits that the aforementioned rejection to claim 11 has been traversed, and respectfully requests that the rejection to claim 11 be withdrawn.

III. Claim Rejections 35 U.S.C. § 102

Requirements for Prima Facie Anticipation

A general definition of *prima facie* unpatentability is provided at 37 C.F.R. §1.56(b)(2)(ii):

> A *prima facie* case of unpatentability is established when the information *compels a conclusion* that a claim is unpatentable under the preponderance of evidence, burden-of-proof standard, giving each term in the claim its broadest reasonable construction consistent with the specification, and before any consideration is given to evidence which may be submitted in an attempt to establish a contrary conclusion of patentability. (*emphasis added*)

"Anticipation requires the disclosure in a single prior art reference of each element of the claim under consideration." *W.L. Gore & Associates v. Garlock, Inc.*, 721 F.2d 1540, 220 USPQ 303, 313 (Fed. Cir. 1983) (citing *Soundscriber Corp. v. United States*, 360 F.2d 954, 960, 148 USPQ 298, 301 (Ct. Cl.), *adopted*, 149 USPQ 640 (Ct. Cl. 1966)), *cert. denied*, 469 U.S. 851 (1984). Thus, to anticipate the applicants' claims, the reference cited by the Examiner must disclose each element recited therein. "There must be no difference between the claimed invention and the reference disclosure, as viewed by a person of ordinary skill in the field of the invention." *Scripps Clinic & Research Foundation v. Genentech, Inc.*, 927 F.2d 1565, 18 USPQ 2d 1001, 1010 (Fed. Cir. 1991).

To overcome the anticipation rejection, the Applicant needs to only demonstrate that not all elements of a *prima facie* case of anticipation have been met, *i.e.*, show that the prior art reference cited by the Examiner fails to disclose every element in each of the applicants' claims. "If the examination at the initial

state does not produce a prima face case of unpatentability, then without more the applicant is entitled to grant of the patent." *In re Oetiker*, 977 F.2d 1443, 24 USPQ 2d 1443, 1444 (Fed. Cir. 1992).

Widrow

Claim 1-20 were rejected under 35 U.S.C. 102(b) as being anticipated by Widrow et al. (U.S. Patent 3, 222, 654, herein referred to as Widrow). The Examiner suggested that the Applicant review the entire teaching of Widrow, as its entire teachings have been relied upon as a basis for the Examiner's rejection. The Examiner stated that when referring to a column and line number of the reference, the following nomenclature is used: CX, LY-Z representing column X, lines Y-Z.

Regarding claim 1, the Examiner asserted that Widrow discloses a system, comprising: a physical neural network (citing C **1**- **12** of Widrow, particularly C 1, L 10-14, and L 40-48, where it describes:*" an adaptive or learning logic network automatically modifies its own structure,"* where its physical properties are discussed in later paragraphs and earlier figures) comprising a liquid state machine (citing Widrow, C 1-12, particularly C 4, L34-55, where it discusses the electrode and liquid electrolyte that changes state to reflect changes in information, via resistivity), wherein said physical neural network comprises molecular connections located within a dielectric solvent between pre-synaptic and post-synaptic electrodes thereof (citing Widrow, C 1-12, particularly C 4, L 35 through L 65, where it discusses leads **21** and **22** as pre- and post—synaptic electrodes thereof), such that said molecular connections are strengthened or weakened according to an application of an electric field, a frequency or a combination thereof to provide physical neural network connections thereof (citing Widrow, C 1-12, particularly C 4, L 24-57: also C 4, L 49-55, where a frequency is inherent in an alternating current).

The Applicant respectfully disagrees with this assessment. Applicant's amended claim 1 is directed toward the following claim limitations: A <u>neural</u> system <u>based on nanotechnology</u>, comprising: a <u>physical neural network</u> comprising a <u>liquid state machine</u>, wherein said physical neural network comprises <u>nanotechnology based connections</u> located within a <u>dielectric solvent</u> between pre-synaptic and post-synaptic electrodes thereof, such that said nanotechnology-based connections are strengthened or weakened according to an application of an <u>electric field</u>, a <u>frequency</u> or a <u>combination thereof</u> to provide physical <u>neural network connections</u> thereof.

The Examiner cited C 4, L34-55 in attempt to argue that Widrow teaches an LSM (Liquid State Machine) as <u>taught</u> by Applicant's invention. The Applicant provides a particular teaching for an LSM at, for example, paragraphs [00328] – [00329] of Applicant's specification as follows:

> [00328] FIG. 39 illustrates a system 3900 of interconnected neural circuitry referred to in the art as a Liquid State Machine, which can be adapted for use in accordance with an alternative embodiment of the present invention. Physical neural network 3900 thus comprises a Knowm™ enabled liquid state machine. System 3900 generally describes a neural network learning mechanism which can be applied to a physical neural network formed utilizing nanotechnology, as described herein. Such a network generally consists of two or more distinct neural modules. Inputs are presented to the first module, referred to as a Liquid State Machine or LSM. The LSM is generally a randomly connected network of neural circuits. Although the connections may be random, this is not always the case. Generally, the exact nature of the connections are not as important as the statistics of the connection, such as the amount of interconnectivity. However such a LSM is connected, its sole purpose is to provide what is referred to in the art as an "analog fading memory". In a liquid state machine, memory tends to fade, similar to the fading of ripples associated with liquid, such as water, as a result of input (e.g., a rock thrown in a pond) to the liquid or water at various times and locations thereof.
>
> [00329] The LSM can store, via patterns of neural activations, its recent past history. Other types of neural circuits can be utilized to extract the "state" of the LSM. A state-extracting neural circuit can be accomplished by a very simple learning neuron, such as, for example, a perceptron. Such perceptrons can adjust their synaptic weights so as to produce a desired output. Such perceptrons can be referred to as a "read-out" neuron. The exact rule that the read-out neurons utilize may vary, but in general such read-out neurons can form a simple linear mapping between the neural circuits within the LSM and the read-out neuron output.

There is simply no teaching in Widrow of an LSM that stores, via patterns of neural activations, its recent past history, nor of an LSM that provides "analog fading memory". Contrary to the Examiner's assertion, C 4, L34-55 of Widrow and the discussion of the electrode and liquid electrolyte that changes state to reflect changes in information, via resistivity, of Widrow, is not an LSM as taught by Applicant's invention. The Examiner has seemingly interpreted a liquid state machine to mean that the device exists in a liquid when in fact the term is used to describe the dynamics of the neural algorithm and has nothing to do with liquid. The electrode, liquid electrolyte and resistivity of Widrow do not result in a device that can store, via patterns of neural activations, its recent past history. In fact, this is impossible because the circuit(s) disclosed by Windrow do not possess the correct topology to function as a Liquid State Machine. More specifically, a liquid state machine requires feedback to circulate neural activations within the network to act as an analog fading memory. Feed-forward neural networks do not possess these feedback connections and consequently do not provide for "analog fading memory" as taught by Applicant's invention. As such, the Applicant respectfully submits that Widrow simply does not provide for an LSM.

Additionally, Widrow does not disclose, suggest or teach a "physical neural network" as taught by Applicant's invention. Applicant's specification refers to particular type of physical neural network, one which is based on nanotechnology. Widrow does not provide for a teaching and/or disclosure or such molecular technology (e.g., nanotechnology) as a basis for forming a physical neural network. In particular, Widrow does not provide a teaching for a nanotechnology-based neural network in which molecular neural connections are formed in a dielectric solution. C 1-12 of Widrow does not provide for any teaching of neural network connections formed in a dielectric solution. Additionally, C 1, L 10-14 and L 40-48 of Widrow cited by the Examiner does not provide for any teaching of a physical neural network as taught by Applicant's claims and specification. The mere

presence of "an adaptive or learning logic network that automatically modifies its own structure" does not provide for a disclosure and/or teaching of the physical neural network taught by Applicant's invention. How does an "adaptive or learning logic network" constitute a physical neural network formed from nanotechnology as taught by Applicant's invention?

Regarding the assertion that C 4, L 35 - L 65 of Widrow teach pre- and post-synaptic electrodes, the Applicant notes that C 4, L 35 - L 65 does not provide for any teaching of pre and post synaptic electrodes as taught by Applicant's invention. In fact, C 4, L 35 - L 65 does not even refer to a synapse, let alone a physical neural network. The leads 21 and 22 of Widrow are just that - leads, and do not provide for any teaching of pre and post synaptic electrodes as taught by Applicant's invention, nor any disclosure, hint or suggestion of molecular (e.g., nanotechnology) physical neural network connections formed in a dielectric network and which can be strengthened or weakened according to an application of an electric field, a frequency of a combination thereof. C 4, L 24-27 and C 4, 49-55 does not disclose these features. The Examiner's argument that a frequency is inherent in an alternating current, does not provide for any teaching of the physical neural network connections formed in a dielectric solution as taught by Applicant's invention or the strengthening or weakening of such neural network connections according to an application of an electric field, a frequency of a combination thereof. Changing the alternating current of Widrow does not result in the use of a frequency to alter neural network connections formed in a dielectric solution (Note: Widrow does not teach such a dielectric solution). Widrow simply provides no teaching of using frequency to strengthen or weaken neural network connections formed in a dielectric solution. It should also be pointed out that that the invention disclosed by Widrow and Applicant's invention are based on completely different physical mechanisms, i.e., electrochemical (Widrow) versus electromechanical (Applicant). Any extrinsic similarities are erroneous because the underlying intrinsic

physical mechanisms that enable each device are completely different from one another. One rather apparent example of the different underlying physical mechanisms is simply that the device disclosed by Widrow requires three terminals to operate, whereas the device disclosed by the Applicant requires only two (e.g., a pre- and post-synaptic electrode). The Applicant respectfully asks the examiner to explain how the invention of Widrow can be made to accomplish the tasks of Applicant's invention with the use of only two electrodes?

It is important to note that Widrow also simply does not provide for any teaching of the nanotechnology-based connections of Applicant's invention. The nanotechnology-based connections of Applicant's invention are based on technologies that did not even exist at the time of Widrow. That is, the nanotechnology-based connections of Applicant's invention utilize components such as nanotubes, nanowires, nanoparticles and so forth. Such nanotechnology-based components and process are not taught or disclosed by Widrow, as they did not exist at the time.

It is important to note that Widrow does not provide for any teaching of nanotechnology (or microfabrication for that matter). Applicant's specification, on the other hand, provides for a teaching of nanotechnology (see paragraphs 0016-0017 of Applicant's specification) as follows:

"[0016] The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

[0017] In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. It is, however, becoming increasingly difficult to increase the number of elements on a chip utilizing existing technologies. At the present rate, in the next few years the theoretical limit of silicon-based chips will have been attained. Because the number of elements and components that can be manufactured on a chip determines

the data storage and processing capabilities of microchips, new technologies are required for the development of higher performance chips."

There is absolutely no teaching in Widrow for such nanotechnology. Where are nanometer scale (or less) components taught by Widrow? The device, as disclosed by Widrow, was contained in a glass vile and is implemented on the scale of centimeters, not nanometers. A review of Widrow does not indicate any disclosure of nanometer scale components such as nanotubes, nanowires, nanoparticles and the like. Widrow also does not provide, for example, any disclosure or teaching of nanometer-scale manufacturing processes, materials and devices. The Examiner has not provided any evidence from Widrow which indicates otherwise.

Additionally, it is important to note that Widrow does not even provide any teaching or disclosure of a neural network. Where is a teaching of a neural network in Widrow? Widrow provides no teaching of a neural network as taught by Applicant's invention. There is no hint or suggestion of neural network components such as synapses, neurons and so forth. The "logic memory" taught by Widrow provides no indication of a neural network and in particular, no teaching of a physical neural network as taught by Applicant's invention.

In order to function as a neural network, the device of Widrow must have certain components inherent to a neural network, such as synapses, neurons and so forth. Applicant's specification at paragraphs [009-0014] generally describes some of the features of a neural network and the problems with hardware versus software implementations of neural networks:

Neural networks that have been developed to date are largely software-based. A true neural network (e.g., the human brain) is massively parallel (and therefore very fast computationally) and very adaptable. For example, half of a human brain can suffer a lesion early in its development and not seriously affect its performance. Software simulations are slow because during the learning phase a standard computer must serially calculate connection strengths. When the networks

get larger (and therefore more powerful and useful), the computational time becomes enormous.

For example, networks with 10,000 connections can easily overwhelm a computer. In comparison, the human brain has about 100 billion neurons, each of which can be connected to about 5,000 other neurons. On the other hand, if a network is trained to perform a specific task, perhaps taking many days or months to train, the final useful result can be built or "downloaded" onto a piece of hardware and also mass-produced. Because most problems requiring complex pattern recognition are highly specific, networks are task-specific. Thus, users usually provide their own, task-specific training data.

A number of software simulations of neural networks have been developed. Because software simulations are performed on conventional sequential computers, however, they do not take advantage of the inherent parallelism of neural network architectures. Consequently, they are relatively slow. One frequently used measurement of the speed of a neural network processor is the number of interconnections it can perform per second.

For example, the fastest software simulations available can perform up to approximately 18 million interconnects per second. Such speeds, however, currently require expensive super computers to achieve. Even so, approximately 18 million interconnects per second is still too slow to perform many classes of pattern classification tasks in real time. These include radar target classifications, sonar target classification, automatic speaker identification, automatic speech recognition, electro-cardiogram analysis, etc.

The implementation of neural network systems has lagged somewhat behind their theoretical potential due to the difficulties in building neural network hardware. This is primarily because of the large numbers of neurons and weighted connections required. The emulation of even of the simplest biological nervous systems would require neurons and connections numbering in the millions and/or billions.

Due to the difficulties in constructing such highly interconnected processors, currently available neural network hardware systems have not approached this level of complexity. Another disadvantage of hardware systems is that they typically are often custom designed and configured to implement one particular neural network architecture and are not easily, if at all, reconfigurable in implementing different architectures. A true physical neural network chip, with the learning abilities and connectivity of a biological network, has not yet been designed and successfully implemented.

Widrow does not teach weighted connections, nor neurons, synapse, nor a device which can emulate a simple biological neural network. Again, the Applicant asks, where and how is a neural network taught by Widrow?

The rejection to claim 1 under 35 U.S.C. 102 based on Widrow fails under the aforementioned prima facie anticipation test. That is, Widrow does not provide for the disclosure of each and every claim limitation of Applicant's claim 1. The Applicant reminds the Examiner that in order to succeed in a rejection to a claim under 35 U.S.C. 102, the reference utilized as a basis for the rejection must disclose each and every claim limitation of the rejected claim. If even one claim limitation or feature is missing, no matter how minor, the rejection under 35 U.S.C. 102 fails. Such claim limitations are enabled by Applicant's specification. In the present case, Widrow does not provide for the disclosure of the LSM taught by Applicant's claims AND specification. Widrow also does not provide for a disclosure of the physical neural network (e.g. based on nanotechnology) taught by Applicant's claims and specification. That is, Widrow does not provide for a disclosure of a physical neural network formed from neural network connections formed in a dielectric solution.

The Applicant therefore submits that the rejection to claim 1 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 1.

Regarding claim 2, the Examiner asserted that Widrow discloses the system of claim 1 wherein said liquid state machine comprises a dynamic fading memory mechanism. In support of this argument, the Examiner cited Widrow, C 1-12, particularly C 4, L 59-73, and argued that the process of hysteresis exhibits a fading memory mechanism in which memory is lost through repeated application of the electric field given the particular electrolytic solution described within. The Examiner also cited C 7, L 50-59 wherein the stability mentioned here comments on the memory's predisposition to fade.

The Applicant respectfully disagrees with this assessment. Widrow at C 1-12 and particularly C 4, L 59-73, does not teach a dynamic fading mechanism as taught by Applicant's invention. The dynamic fading memory, as taught by the

Applicant's invention, is a network property, not a synaptic property. In other words, the dynamics of the synaptic connection do not play a significant role in the networks ability to retain a memory trace because the memory trace is retained the pattern of neural activation. The Applicant suggests that the Examiner re-read the Applicant's description of a Liquid State Machine and its use of an analog fading memory, particularly paragraphs 00328 and 00329 where it states:

> "...the exact nature of the connections are not as important as the statistics of the connection, such as the amount of interconnectivity."
>
> And...
>
> "...LSM can store, via patterns of neural activations, its recent past history. "

The Examiner's comparison of an analog fading memory to a hysteresis effect on an electroplating device is irrelevant because it is the pattern of connectivity, not the behavior of a connection element, that is important in an analog fading memory.

The Applicant therefore respectfully requests that the rejection to claim 2 be withdrawn because the rejection does not meet the requirements of the aforementioned prima facie anticipation test.

Regarding claim 3, the Examiner asserted that Widrow discloses the system of claim 1 further comprising a supervised learning mechanism associated with said liquid state machine (citing Widrow, C 1-12, particularly C 1, 34-65 where it discusses the details and reasoning behind the supervised learning method of neural networks), whereby connections strengths of said molecular connections are determined pre-synaptic and post-synaptic electrodes (citing Widrow, C 1-12, particularly C 2, L 13-24, also C 3, L 3-18; also C 4, L 34-55 where it discusses leads **21** and **22** as pre-and post- synaptic electrodes thereof).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 1 apply equally against

the rejection to claim 3. Thus, because claim 3 depends from claim 1 and claim 1 has been traversed as indicated above, the Applicant submits that the rejection to claim 3 is also traversed.

Additionally, the Applicant notes that Widrow could not possibly provide a teaching of strengthening connections via pre- and post-synaptic activity because the device described by Widrow does not modify its resistance via leads 21 and 22 but rather lead 18. The examiners comparison of leads 21 and 22 to a pre-and post-synaptic electrode are incorrect because the device also contains an addition electrode, 18, without which the device will not function. How can a synapse, a two-terminal device, contain three electrodes? How can leads 21 and 22 be used to modify the electrical resistance when it is explicitly stated by Widrow that lead 18 is needed to provide the electroplating material needed to affect the resistance? (Widrow, C 4, L 34-55.). If the device disclosed by Widrow cannot function without lead 18 and the applicant's invention does not contain such a lead, it follows that the examiners remarks neglect the fact that the two devices are extraordinarily different in both fabrication and function. For this fact and also the fact that Widrow provides absolutely no teaching for a Liquid State Machine, The Applicant submits that the rejection to claim 3 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 3.

Regarding claim 4, the Examiner asserted that Widrow discloses the system of claim 3 wherein said supervised learning mechanism comprises at least one perceptron (citing Widrow, C 1-12, particularly C 2, L 40-43 as well as C 3, L 18-47 where it discusses the details of the functions of a perceptron, which is in its simplest embodiment a weighted summer followed by a non-linear output or thresholder).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claims 1 and 3 apply equally

against the rejection to claim 4. Thus, because claim 4 depends from claim 3 and claim 1, and claims 3 and 1 have been traversed as indicated above, the Applicant submits that the rejection to claim 4 is also traversed.

The Applicant also notes that C 2, L 40-43 as well as C 3, L 18-47 of Widrow do not provide for the disclosure of a perceptron as taught by Applicant's invention. Paragraph 00329 of Applicant's invention, for example, indicates that perceptrons adjust their synaptic weights so as to produce a desired output. There is no adjustment of any synaptic weights taking place at C 2, L 40-43 as well as C 3, L 18-47 of Widrow. Where is a synaptic weight even taught by Widrow? As Applicant's specification indications, a perceptron is essentially a "read-out" neuron. The exact rule that the read-out neurons utilize may vary, but in general such read-out neurons can form a simple linear mapping between neural circuits within an LSM and the read-out neuron output. Such features are not taught, suggested or disclosed by Widrow.

Based on the foregoing, the Applicant submits that the rejection to claim 4 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 4.

Regarding claim 5, the Examiner asserted that Widrow discloses the system of claim 3 wherein said supervised learning mechanism learns via feedback obtained from said post-synaptic electrodes. (citing Widrow, C 1-12, particularly C 1, L 45-55 where it refers to the adaptive logic network's prior experience, and the only way for such a system to be aware of its "prior experience is through the use of feedback obtained from the post synaptic electrode; also disclosing that the learning is purely mechanical and thus to reduce the errors to zero, the system must be aware of the actual and desired outputs, thus necessitating feedback).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claims 1 and 3 apply equally against the rejection to claim 5. Thus, because claim 5 depends from claim 3 and

claim 1, and claims 3 and 1 have been traversed as indicated above, the Applicant submits that the rejection to claim 5 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 5 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 5.

Regarding claim 6, the Examiner asserted that Widrow discloses the system of claim 3 wherein said supervised learning mechanism comprises a linear read out mechanism (citing Widrow, C 1-12, particularly C 3, L 17-57, where it discusses the quantizer-thresholding unit, and it's ability to produce a read out mechanism following the linear combinatory summer).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claims 1 and 3 apply equally against the rejection to claim 6. Thus, because claim 6 depends from claim 3 and claim 1, and claims 3 and 1 have been traversed as indicated above, the Applicant submits that the rejection to claim 6 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 6 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 6.

Regarding claim 7, the Examiner asserted that Widrow discloses the system of claim 3 wherein said supervised learning mechanism evolves based on an activity depending learning rule (citing Widrow, C 1-12, particularly C 1, L 36-55).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claims 1 and 3 apply equally against the rejection to claim 7. Thus, because claim 7 depends from claim 3 and claim 1, and claims 3 and 1 have been traversed as indicated above, the Applicant submits that the rejection to claim 7 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 7 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 7.

Regarding claim 8, the Examiner asserted that Widrow discloses the system of claim 3 wherein said supervised learning mechanism evolves based on pre-

synaptic and post-synaptic activity, including a voltage, frequency, or a combination thereof (citing Widrow, C 1-12, particularly C 1, L 45 through C 2, L2 where it discusses the supervised learning mechanism and in C 4, L 24-73 where it discusses the physical properties and mechanisms of the novel adaptive memory element; also C 4, L 49-55, where a frequency is inherent in an alternating current and where it discusses leads **21** and **22** as pre- and post- synaptic electrodes thereof).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claims 1 and 3 apply equally against the rejection to claim 8. Thus, because claim 8 depends from claim 3 and claim 1, and claims 3 and 1 have been traversed as indicated above, the Applicant submits that the rejection to claim 8 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 8 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 8.

Regarding claim 9, the Examiner argued that Widrow discloses the system of claim 1 wherein said molecular connections comprise nanoparticles (citing Widrow, C 1-12, particularly C 4, L 24-73, where it discusses the materials used to achieve electroplating. The reaction occurring at the molecular scale of this system contains particles that are in the order of 10^-9).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 9. Thus, because claim 9 depends from claim 1 and claim 1 has been traversed as indicated above, the Applicant submits that the rejection to claim 9 is also traversed.

The Applicant also points out the Examiner's use of the word "reaction" and notes that Applicant's invention does not rely on a chemical process (i.e., a chemical reaction), but rather an electro-mechanical force created by divergent electric fields. The Examiner's comment that the components of the device disclosed by Widrow are particles in the order of 10^-9 neglects the fact that the

device in its entirety is on the scale of centimeters. The Applicant respectfully points out that all systems in the known universe are constructed from material at the nanometer, or sub-nanometer scale, but this does not make the systems or devices nano-scale. For this fact and also that the systems disclosed by the Applicant's invention and Widrow bear no similarity in operation or fabrications, the Applicant submits that the rejection to claim 9 is traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 9.

Regarding claim 10, the Examiner argued that Widrow discloses the system of claim 1 wherein said molecular connections comprise molecules (citing Widrow, C 1-12, particularly C 4, L 24-73 where it discusses the materials used to achieve electroplating, however it remains inherently apparent that molecular connections comprise molecules).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 10. Thus, because claim 10 depends from claim 1, and claim 1 has been traversed as indicated above, the Applicant submits that the rejection to claim 10 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 10 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 10.

Regarding claim 11, the Examiner argued that Widrow disclose the system of claim 1 further comprising a connection network also comprising a plurality of said molecular connections (the Examiner argued that it remains inherent for a neural network to comprise a connection network as one can not exist with its respective connections) wherein molecular nanoconnection thereof can be strengthened or weakened according to an application of said electric field or said frequency (citing Widrow, C 1-12, particularly C 4, L 24-73 where it discusses the physical properties and mechanisms of the novel adaptive memory element; also C 4, L 49-55, where a frequency is inherent in an alternating current. The Examiner asserted that

strengthening and weakening corresponds to the amount of deposit on the substrate, as more or less will strengthen or weaken the nanoconnections thereof).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 1 apply equally against the rejection to claim 11. Thus, because claim **11** depends from claim **1**, and claim 1 has been traversed as indicated above, the Applicant submits that the rejection to claim 11 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 11 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 11.

Regarding claim 12, the Examiner asserted that Widrow discloses a system, comprising: a physical neural network (citing Widrow C 1, L 10-14. and L 40-48, where it describes "an adaptive or learning logic network automatically modifies its own structure, "where its physical properties are discussed in later paragraphs and earlier figures) comprising: a liquid state machine (citing Widrow C 1-12, particularly C 4, L34-55, where it discusses the electrode and liquid electrolyte that changes state to reflect changes in information, via resistivity), wherein said physical neural network comprises molecular connections located within a dielectric solvent between pre-synaptic and post-synaptic electrodes thereof (citing Widrow C 1-12, particularly C 4, L 35 through L 65 where it discusses leads **21** and **22** as pr and post- synaptic electrodes thereof), such that said molecular connections are strengthened or weakened according to an application of an electric field, a frequency or a combination thereof to provide physical neural network connections thereof (citing Widrow C 1-12, particularly C 4, L 24-57; also C 4, L 49-55, where a frequency is inherent in an alternating current); and a supervised learning mechanism associated with said liquid state machine (citing Widrow C 1-12, particularly C 1, L 34-65 where it discusses the details and reasoning behind the supervised learning method of neural networks), whereby connections strengths of said molecular connections are determined by pre-synaptic and postsynaptic

activity respectively associated with said pre-synaptic and post-synaptic electrodes (citing Widrow C 1-12. particularly C 2, L 13-24, also C 3, L 3-18, also C4, L 34-55 where it discusses leads **21** and **22** as pre- and post-synaptic electrodes thereof), wherein said liquid state machine comprises a dynamic fading memory mechanism (citing Widrow C 1-12, particularly C 4, L 59-73, the process of hysteresis exhibits a fading memory mechanism in which memory is lost through repeated application of the electric field given the particular electrolytic solution described within. The Examiner also cited in C 7, L 50-59 of Widrow wherein the stability mentioned here comments on the memory's predisposition to fade).

The Applicant respectfully disagrees with this assessment. Applicant's amended claim 12 is directed toward the following claim limitations: A neural system based on nanotechnology, comprising: a physical neural network comprising a liquid state machine, wherein said physical neural network comprises nanotechnology based connections located within a dielectric solvent between pre-synaptic and post-synaptic electrodes thereof, such that said nanotechnology-based connections are strengthened or weakened according to an application of an electric field, a frequency or a combination thereof to provide physical neural network connections thereof.

The Examiner cited C 4, L34-55 in attempt to argue that Widrow teaches an LSM (Liquid State Machine) as taught by Applicant's invention. The Applicant provides a particular teaching for an LSM at, for example, paragraphs [00328] – [00329] of Applicant's specification as follows:

[00328] FIG. 39 illustrates a system 3900 of interconnected neural circuitry referred to in the art as a Liquid State Machine, which can be adapted for use in accordance with an alternative embodiment of the present invention. Physical neural network 3900 thus comprises a Knowm™ enabled liquid state machine. System 3900 generally describes a neural network learning mechanism which can be applied to a physical neural network formed utilizing nanotechnology, as described herein. Such a network generally consists of two or more distinct neural modules. Inputs are presented to the first module, referred to as a Liquid State Machine or LSM. The LSM is generally a randomly connected network of neural circuits. Although the connections may be random, this is not always the case. Generally, the exact nature of the connections are not as important as the statistics of the

connection, such as the amount of interconnectivity. However such a LSM is connected, its sole purpose is to provide what is referred to in the art as an "analog fading memory". In a liquid state machine, memory tends to fade, similar to the fading of ripples associated with liquid, such as water, as a result of input (e.g., a rock thrown in a pond) to the liquid or water at various times and locations thereof.

[00329] The LSM can store, via patterns of neural activations, its recent past history. Other types of neural circuits can be utilized to extract the "state" of the LSM. A state-extracting neural circuit can be accomplished by a very simple learning neuron, such as, for example, a perceptron. Such perceptrons can adjust their synaptic weights so as to produce a desired output. Such perceptrons can be referred to as a "read-out" neuron. The exact rule that the read-out neurons utilize may vary, but in general such read-out neurons can form a simple linear mapping between the neural circuits within the LSM and the read-out neuron output.

There is simply <u>no</u> teaching in Widrow of an LSM that <u>stores</u>, via <u>patterns</u> of <u>neural activations</u>, its recent past history, nor of an LSM that provides "analog fading memory". Contrary to the Examiner's assertion, C 4, L34-55 of Widrow and the discussion of the electrode and liquid electrolyte that changes state to reflect changes in information, via resistivity, of Widrow, is <u>not</u> an LSM <u>as taught</u> by Applicant's invention. The Examiner has seemingly interpreted a liquid state machine to mean that the device exists in a liquid when in fact the term is used to describe the dynamics of the neural algorithm and has nothing to do with liquid. The electrode, liquid electrolyte and resistivity of Widrow do not result in a device that can <u>store</u>, via <u>patterns</u> of <u>neural activations</u>, its <u>recent past history</u>. In fact, this is impossible because the circuit(s) disclosed by Windrow do <u>not</u> possess the correct topology to function as a Liquid State Machine. More specifically, a liquid state machine requires feedback to circulate neural activations within the network to act as an analog <u>fading memory</u>. Feed-forward neural networks do not possess these feedback connections and consequently do <u>not</u> provide for "analog fading memory" as taught by Applicant's invention. As such, the Applicant respectfully submits that Widrow simply does not provide for an LSM.

Additionally, Widrow does not disclose, suggest or teach a "physical neural network" as taught by Applicant's invention. Applicant's specification refers to

particular type of physical neural network, one which is based on nanotechnology. Widrow does not provide for a teaching and/or disclosure or such molecular technology (e.g., nanotechnology) as a basis for forming a physical neural network. In particular, Widrow does not provide a teaching for a nanotechnology-based neural network in which molecular neural connections are formed in a dielectric solution. C 1-12 of Widrow does not provide for any teaching of neural network connections formed in a dielectric solution. Additionally, C 1, L 10-14 and L 40-48 of Widrow cited by the Examiner does not provide for any teaching of a physical neural network as taught by Applicant's claims and specification. The mere presence of "an adaptive or learning logic network that automatically modifies its own structure" does not provide for a disclosure and/or teaching of the physical neural network taught by Applicant's invention. How does an "adaptive or learning logic network" constitute a physical neural network formed from nanotechnology as taught by Applicant's invention?

Regarding the assertion that C 4, L 35 – L 65 of Widrow teach pre- and post-synaptic electrodes, the Applicant notes that C 4, L 35 – L 65 does not provide for any teaching of pre and post synaptic electrodes as taught by Applicant's invention. In fact, C 4, L 35 – L 65 does not even refer to a synapse, let alone a physical neural network. The leads 21 and 22 of Widrow are just that – leads, and do not provide for any teaching of pre and post synaptic electrodes as taught by Applicant's invention, nor any disclosure, hint or suggestion of molecular (e.g., nanotechnology) physical neural network connections formed in a dielectric network and which can be strengthened or weakened according to an application of an electric field, a frequency of a combination thereof. C 4, L 24-27 and C 4, 49-55 does not disclose these features. The Examiner's argument that a frequency is inherent in an alternating current, does not provide for any teaching of the physical neural network connections formed in a dielectric solution as taught by Applicant's invention or the strengthening or weakening of such neural network connections

according to an application of an electric field, a frequency of a combination thereof. Changing the alternating current of Widrow does not result in the use of a frequency to alter neural network connections formed in a dielectric solution (Note: Widrow does not teach such a dielectric solution). Widrow simply provides no teaching of using frequency to strengthen or weaken neural network connections formed in a dielectric solution. It should also be pointed out that that the invention disclosed by Widrow and Applicant's invention are based on completely different physical mechanisms, i.e., electrochemical (Widrow) versus electromechanical (Applicant). Any extrinsic similarities are erroneous because the underlying intrinsic physical mechanisms that enable each device are completely different from one another. One rather apparent example of the different underlying physical mechanisms is simply that the device disclosed by Widrow requires three terminals to operate, whereas the device disclosed by the Applicant requires only two (e.g., a pre- and post-synaptic electrode). The Applicant respectfully asks the examiner to explain how the invention of Widrow can be made to accomplish the tasks of Applicant's invention with the use of only two electrodes?

It is important to note that Widrow also simply does not provide for any teaching of the nanotechnology-based connections of Applicant's invention. The nanotechnology-based connections of Applicant's invention are based on technologies that did not even exist at the time of Widrow. That is, the nanotechnology-based connections of Applicant's invention utilize components such as nanotubes, nanowires, nanoparticles and so forth. Such nanotechnology-based components and process are not taught or disclosed by Widrow, as they did not exist at the time.

It is important to note that Widrow does not provide for any teaching of nanotechnology (or microfabrication for that matter). Applicant's specification, on the other hand, provides for a teaching of nanotechnology (see paragraphs 0016-0017 of Applicant's specification) as follows:

"[0016] The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

[0017] In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. It is, however, becoming increasingly difficult to increase the number of elements on a chip utilizing existing technologies. At the present rate, in the next few years the theoretical limit of silicon-based chips will have been attained. Because the number of elements and components that can be manufactured on a chip determines the data storage and processing capabilities of microchips, new technologies are required for the development of higher performance chips."

There is absolutely no teaching in Widrow for such nanotechnology. Where are nanometer scale (or less) components taught by Widrow? The device, as disclosed by Widrow, was contained in a glass vile and is implemented on the scale of centimeters, not nanometers. A review of Widrow does not indicate any disclosure of nanometer scale components such as nanotubes, nanowires, nanoparticles and the like. Widrow also does not provide, for example, any disclosure or teaching of nanometer-scale manufacturing processes, materials and devices. The Examiner has not provided any evidence from Widrow which indicates otherwise.

Additionally, it is important to note that Widrow does not even provide any teaching or disclosure of a neural network. Where is a teaching of a neural network in Widrow? Widrow provides no teaching of a neural network as taught by Applicant's invention. There is no hint or suggestion of neural network components such as synapses, neurons and so forth. The "logic memory" taught by Widrow provides no indication of a neural network and in particular, no teaching of a physical neural network as taught by Applicant's invention.

In order to function as a neural network, the device of Widrow must have certain components inherent to a neural network, such as synapses, neurons and so forth. Applicant's specification at paragraphs [009-0014] generally describes some of the features of a neural network and the problems with hardware versus software implementations of neural networks:

> Neural networks that have been developed to date are largely software-based. A true neural network (e.g., the human brain) is massively parallel (and therefore very fast computationally) and very adaptable. For example, half of a human brain can suffer a lesion early in its development and not seriously affect its performance. Software simulations are slow because during the learning phase a standard computer must serially calculate connection strengths. When the networks get larger (and therefore more powerful and useful), the computational time becomes enormous.
>
> For example, networks with 10,000 connections can easily overwhelm a computer. In comparison, the human brain has about 100 billion neurons, each of which can be connected to about 5,000 other neurons. On the other hand, if a network is trained to perform a specific task, perhaps taking many days or months to train, the final useful result can be built or "downloaded" onto a piece of hardware and also mass-produced. Because most problems requiring complex pattern recognition are highly specific, networks are task-specific. Thus, users usually provide their own, task-specific training data.
>
> A number of software simulations of neural networks have been developed. Because software simulations are performed on conventional sequential computers, however, they do not take advantage of the inherent parallelism of neural network architectures. Consequently, they are relatively slow. One frequently used measurement of the speed of a neural network processor is the number of interconnections it can perform per second.
>
> For example, the fastest software simulations available can perform up to approximately 18 million interconnects per second. Such speeds, however, currently require expensive super computers to achieve. Even so, approximately 18 million interconnects per second is still too slow to perform many classes of pattern classification tasks in real time. These include radar target classifications, sonar target classification, automatic speaker identification, automatic speech recognition, electro-cardiogram analysis, etc.
>
> The implementation of neural network systems has lagged somewhat behind their theoretical potential due to the difficulties in building neural network hardware. This is primarily because of the large numbers of neurons and weighted connections

required. The emulation of even of the simplest biological nervous systems would require neurons and connections numbering in the millions and/or billions.

Due to the difficulties in constructing such highly interconnected processors, currently available neural network hardware systems have not approached this level of complexity. Another disadvantage of hardware systems is that they typically are often custom designed and configured to implement one particular neural network architecture and are not easily, if at all, reconfigurable in implementing different architectures. A true physical neural network chip, with the learning abilities and connectivity of a biological network, has not yet been designed and successfully implemented.

Widrow does not teach weighted connections, nor neurons, synapse, nor a device which can emulate a simple biological neural network. Again, the Applicant asks, where and how is a neural network taught by Widrow?

Additionally, the Applicant notes that Widrow could not possibly provide a teaching of strengthening connections via pre- and post-synaptic activity because the device described by Widrow does not modify its resistance via leads 21 and 22 but rather lead 18. The examiners comparison of leads 21 and 22 to a pre-and post-synaptic electrode are incorrect because the device also contains an addition electrode, 18, without which the device will not function. How can a synapse, a two-terminal device, contain three electrodes? How can leads 21 and 22 be used to modify the electrical resistance when it is explicitly stated by Widrow that lead 18 is needed to provide the electroplating material needed to affect the resistance? (Widrow, C 4, L 34-55.). If the device disclosed by Widrow cannot function without lead 18 and the applicant's invention does not contain such a lead, it follows that the examiners remarks neglect the fact that the two devices are extraordinarily different in both fabrication and function.

The rejection to claim 12 under 35 U.S.C. 102 based on Widrow fails under the aforementioned prima facie anticipation test. That is, Widrow does not provide for the disclosure of each and every claim limitation of Applicant's claim 12. The Applicant reminds the Examiner that in order to succeed in a rejection to a claim

under 35 U.S.C. 102, the reference utilized as a basis for the rejection must disclose each and every claim limitation of the rejected claim. If even one claim limitation or feature is missing, no matter how minor, the rejection under 35 U.S.C. 102 fails. Such claim limitations are enabled by Applicant's specification. In the present case, Widrow does not provide for the disclosure of the LSM taught by Applicant's claims AND specification. Widrow also does not provide for a disclosure of the physical neural network (e.g. based on nanotechnology) taught by Applicant's claims and specification. That is, Widrow does not provide for a disclosure of a physical neural network formed from neural network connections formed in a dielectric solution.

The Applicant therefore submits that the rejection to claim 12 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 12.

Regarding claim 13, the Examiner argued that Widrow discloses the system of claim 12 wherein said supervised learning mechanism comprises at least one perceptron (citing Widrow, C 1-12, particularly C 2, L 40-43 as well as C 3, L 18-47 where it discusses the details of the functions of a perceptron, which is in its simplest embodiment a weighted summer followed by a non-linear output or thresholder).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 12 apply equally against the rejection to claim 13. Thus, because claim 13 depends from claim 12, and claim 12 has been traversed as indicated above, the Applicant submits that the rejection to claim 13 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 13 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 13.

Regarding claim 14, the Examiner argued that Widrow discloses the system of claim 12 wherein said supervised learning mechanism learns via feedback obtained from said pre-synaptic and post-synaptic electrodes. (citing Widrow, C 1-12, particularly C 1, L 45-55 where it refers to the adaptive logic network's prior experience, and the only way for such a system to be aware of its 'prior experience is through the use of feedback obtained from the post synaptic electrode; also see C 4, L 3-19 where the operation of the training mechanism is further discussed, also disclosing that the learning is purely mechanical and thus to reduce the errors to zero, the system must be aware of the actual and desired outputs, thus necessitating feedback).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 12 apply equally against the rejection to claim 14. Thus, because claim 14 depends from claim 12, and claim 12 has been traversed as indicated above, the Applicant submits that the rejection to claim 14 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 14 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 14.

Regarding claim 15, the Examiner argued that Widrow discloses the system of claim 12 wherein said supervised learning mechanism comprises a linear read out mechanism (citing Widrow, C 1-12, particularly C 3, L 17-57 where it discusses the quantizer-thresholding unit, and it's ability to produce a read out mechanism following the linear combinatory summer.)

he Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 12 apply equally against the rejection to claim 15. Thus, because claim 15 depends from claim 12, and claim 12 has been traversed as indicated above, the Applicant submits that the rejection to claim 15 is also traversed. Based on the foregoing, the Applicant

submits that the rejection to claim 15 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 15.

Regarding claim 16, the Examiner argued that Widrow discloses the system of claim 15 wherein said supervised learning mechanism evolves based on post-synaptic activity, including a voltage, frequency, or a combination thereof (citing Widrow, C 1-12, particularly C 1 L 45 through C 2, L 2 where it discusses the supervised learning mechanism and in C 4, L 24-73 where it discusses the physical properties and mechanisms of the novel adaptive memory element; also C 4, L 49-55, where a frequency is inherent in an alternating current).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 15 apply equally against the rejection to claim 16. Thus, because claim 16 depends from claim 15, and claim 15 has been traversed as indicated above, the Applicant submits that the rejection to claim 16 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 16 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 16.

Regarding claim 17, the Examiner argued that Widrow discloses the system of claim 12 wherein said molecular connections comprise nanoconnections (citing Widrow, C 1-12, particularly C 4, L 24-73, where it discusses the materials used to achieve electroplating. The Examiner asserted that the reaction occurring at the molecular scale of this system contains particles that are in the order of 10^9 that bond in accordance with the occurring chemical reaction).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 12 apply equally against the rejection to claim 17. Thus, because claim 17 depends from claim 12, and claim 12 has been traversed as indicated above, the Applicant submits that the rejection to claim 17 is also traversed. Based on the foregoing, the Applicant

submits that the rejection to claim 17 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 17.

Regarding claim 18, the Examiner argued that Widrow discloses a system, comprising: a physical neural network (citing Widrow, C 1-12, particularly C 1, L 10-14, and L 40-48, where it describes "an adaptive or learning logic network automatically modifies its own structure, "where its physical properties are discussed in later paragraphs and earlier figures) comprising a liquid state machine (citing Widrow, C 1-12, particularly C 4, L 34-55, where it discusses the electrode and liquid electrolyte that changes state to reflect changes in information, via resistivity), wherein said physical neural network is formed utilizing nanotechnology (citing Widrow, C 1-12, particularly C 1, L 29 through C 2, L 27 where it discusses adaptive memory elements of the type therein described and their role in logic networks becoming increasingly complex in size, thus requiring numerous amounts of memory elements. The nanotechnology is utilized in the form of chemical reactions at the substrate and electrode), including nanoconnections (citing Widrow, C 1-12, particularly C 4, L 24-73, where it discusses the materials used to achieve electroplating. The reaction occurring at the molecular scale of this system contains particles that are in the order of 10^9 that bond in accordance with the occurring chemical reaction) located within a dielectric solvent between pre-synaptic and post-synaptic electrodes thereof (citing Widrow, C 1-12, particularly C 4, L 35 through L 65), such that said nanoconnections are strengthened or weakened according to an application of an electric field, a frequency or a combination thereof (citing Widrow, C 1-12, particularly C 4, L 24-57: also C 4, L 49-55, where a frequency is inherent in an alternating current) to provide a physical neural network thereof; and a supervised learning mechanism associated with said liquid state machine (citing Widrow, C 1-12, particularly C 1, L 34-65 where it discusses the details and reasoning behind the supervised learning method of neural networks), whereby connections strengths of said nanoconnections are determined by pre-

synaptic and post synaptic activity respectively associated with said pre-synaptic and post-synaptic electrodes (citing Widrow, C 1-12, particularly C 2, L 13-24, also C 3, L 3-18), wherein said liquid state machine comprises a dynamic fading memory mechanism (citing Widrow, C 1-12, particularly C 4, L 59-73, the process of hysteresis exhibits a fading memory mechanism in which memory is lost through repeated application of the electric field given the particular electrolytic solution described within. Also the Examiner cited C 7, L 50-59 wherein the stability mentioned here comments on the memory's predisposition to fade).

The Applicant respectfully disagrees with this assessment. Applicant's claim 18 is generally directed toward the following claim limitations: A neural system based on nanotechnology, comprising: a physical neural network comprising a liquid state machine, wherein said physical neural network comprises nanotechnology based connections located within a dielectric solvent between pre-synaptic and post-synaptic electrodes thereof, such that said nanotechnology-based connections are strengthened or weakened according to an application of an electric field, a frequency or a combination thereof to provide physical neural network connections thereof. Claim 18 also includes the claim limitations of a supervised learning mechanism associated with said liquid state machine, whereby connections strengths of said nanoconnections are determined by pre-synaptic and post-synaptic activity respectively associated with said pre-synaptic and post-synaptic electrodes, wherein said liquid state machine comprises a dynamic fading memory mechanism.

The Examiner cited C 4, L34-55 in attempt to argue that Widrow teaches an LSM (Liquid State Machine) as taught by Applicant's invention. The Applicant provides a particular teaching for an LSM at, for example, paragraphs [00328] – [00329] of Applicant's specification as follows:

[00328] FIG. 39 illustrates a system 3900 of interconnected neural circuitry referred to in the art as a Liquid State Machine, which can be adapted for use in accordance with an alternative embodiment of the present invention. Physical neural network 3900 thus

comprises a Knowm™ enabled liquid state machine. System 3900 generally describes a neural network learning mechanism which can be applied to a physical neural network formed utilizing nanotechnology, as described herein. Such a network generally consists of two or more distinct neural modules. Inputs are presented to the first module, referred to as a Liquid State Machine or LSM. The LSM is generally a randomly connected network of neural circuits. Although the connections may be random, this is not always the case. Generally, the exact nature of the connections are not as important as the statistics of the connection, such as the amount of interconnectivity. However such a LSM is connected, its sole purpose is to provide what is referred to in the art as an "analog fading memory". In a liquid state machine, memory tends to fade, similar to the fading of ripples associated with liquid, such as water, as a result of input (e.g., a rock thrown in a pond) to the liquid or water at various times and locations thereof.

[00329] The LSM can store, via patterns of neural activations, its recent past history. Other types of neural circuits can be utilized to extract the "state" of the LSM. A state-extracting neural circuit can be accomplished by a very simple learning neuron, such as, for example, a perceptron. Such perceptrons can adjust their synaptic weights so as to produce a desired output. Such perceptrons can be referred to as a "read-out" neuron. The exact rule that the read-out neurons utilize may vary, but in general such read-out neurons can form a simple linear mapping between the neural circuits within the LSM and the read-out neuron output.

There is simply <u>no</u> teaching in Widrow of an LSM that <u>stores</u>, via <u>patterns</u> of <u>neural activations</u>, its recent past history, nor of an LSM that provides "analog fading memory". Contrary to the Examiner's assertion, C 4, L34-55 of Widrow and the discussion of the electrode and liquid electrolyte that changes state to reflect changes in information, via resistivity, of Widrow, is <u>not</u> an LSM <u>as taught</u> by Applicant's invention. The Examiner has seemingly interpreted a liquid state machine to mean that the device exists in a liquid when in fact the term is used to describe the dynamics of the neural algorithm and has nothing to do with liquid. The electrode, liquid electrolyte and resistivity of Widrow do not result in a device that can <u>store</u>, via <u>patterns</u> of <u>neural activations</u>, its <u>recent past history</u>. In fact, this is impossible because the circuit(s) disclosed by Windrow do <u>not</u> possess the correct topology to function as a Liquid State Machine. More specifically, a liquid state machine requires feedback to circulate neural activations within the network to act as an analog <u>fading memory</u>. Feed-forward neural networks do not possess these feedback connections and consequently do <u>not</u> provide for "analog fading

memory" as taught by Applicant's invention. As such, the Applicant respectfully submits that Widrow simply does not provide for an LSM.

Additionally, Widrow does not disclose, suggest or teach a "physical neural network" as taught by Applicant's invention. Applicant's specification refers to particular type of physical neural network, one which is based on nanotechnology. Widrow does not provide for a teaching and/or disclosure or such molecular technology (e.g., nanotechnology) as a basis for forming a physical neural network. In particular, Widrow does not provide a teaching for a nanotechnology-based neural network in which molecular neural connections are formed in a dielectric solution. C 1-12 of Widrow does not provide for any teaching of neural network connections formed in a dielectric solution. Additionally, C 1, L 10-14 and L 40-48 of Widrow cited by the Examiner does not provide for any teaching of a physical neural network as taught by Applicant's claims and specification. The mere presence of "an adaptive or learning logic network that automatically modifies its own structure" does not provide for a disclosure and/or teaching of the physical neural network taught by Applicant's invention. How does an "adaptive or learning logic network" constitute a physical neural network formed from nanotechnology as taught by Applicant's invention?

Regarding the assertion that C 4, L 35 – L 65 of Widrow teach pre- and post-synaptic electrodes, the Applicant notes that C 4, L 35 – L 65 does not provide for any teaching of pre and post synaptic electrodes as taught by Applicant's invention. In fact, C 4, L 35 – L 65 does not even refer to a synapse, let alone a physical neural network. The leads 21 and 22 of Widrow are just that – leads, and do not provide for any teaching of pre and post synaptic electrodes as taught by Applicant's invention, nor any disclosure, hint or suggestion of molecular (e.g., nanotechnology) physical neural network connections formed in a dielectric network and which can be strengthened or weakened according to an application of an electric field, a frequency of a combination thereof. C 4, L 24-27 and C 4, 49-55

does not disclose these features. The Examiner's argument that a frequency is inherent in an alternating current, does not provide for any teaching of the physical neural network connections formed in a dielectric solution as taught by Applicant's invention or the strengthening or weakening of such neural network connections according to an application of an electric field, a frequency of a combination thereof. Changing the alternating current of Widrow does not result in the use of a frequency to alter neural network connections formed in a dielectric solution (Note: Widrow does not teach such a dielectric solution). Widrow simply provides no teaching of using frequency to strengthen or weaken neural network connections formed in a dielectric solution. It should also be pointed out that that the invention disclosed by Widrow and Applicant's invention are based on completely different physical mechanisms, i.e., electrochemical (Widrow) versus electromechanical (Applicant). Any extrinsic similarities are erroneous because the underlying intrinsic physical mechanisms that enable each device are completely different from one another. One rather apparent example of the different underlying physical mechanisms is simply that the device disclosed by Widrow requires three terminals to operate, whereas the device disclosed by the Applicant requires only two (e.g., a pre- and post-synaptic electrode). The Applicant respectfully asks the examiner to explain how the invention of Widrow can be made to accomplish the tasks of Applicant's invention with the use of only two electrodes?

It is important to note that Widrow also simply does not provide for any teaching of the nanotechnology-based connections of Applicant's invention. The nanotechnology-based connections of Applicant's invention are based on technologies that did not even exist at the time of Widrow. That is, the nanotechnology-based connections of Applicant's invention utilize components such as nanotubes, nanowires, nanoparticles and so forth. Such nanotechnology-based components and process are not taught or disclosed by Widrow, as they did not exist at the time.

It is important to note that Widrow does not provide for any teaching of nanotechnology (or microfabrication for that matter). Applicant's specification, on the other hand, provides for a teaching of nanotechnology (see paragraphs 0016-0017 of Applicant's specification) as follows:

"[0016] The term "Nanotechnology" generally refers to nanometer-scale manufacturing processes, materials and devices, as associated with, for example, nanometer-scale lithography and nanometer-scale information storage. Nanometer-scale components find utility in a wide variety of fields, particularly in the fabrication of microelectrical and microelectromechanical systems (commonly referred to as "MEMS"). Microelectrical nano-sized components include transistors, resistors, capacitors and other nano-integrated circuit components. MEMS devices include, for example, micro-sensors, micro-actuators, micro-instruments, micro-optics, and the like.

[0017] In general, nanotechnology presents a solution to the problems faced in the rapid pace of computer chip design in recent years. According to Moore's law, the number of switches that can be produced on a computer chip has doubled every 18 months. Chips now can hold millions of transistors. It is, however, becoming increasingly difficult to increase the number of elements on a chip utilizing existing technologies. At the present rate, in the next few years the theoretical limit of silicon-based chips will have been attained. Because the number of elements and components that can be manufactured on a chip determines the data storage and processing capabilities of microchips, new technologies are required for the development of higher performance chips."

There is absolutely no teaching in Widrow for such nanotechnology. Where are nanometer scale (or less) components taught by Widrow? The device, as disclosed by Widrow, was contained in a glass vile and is implemented on the scale of centimeters, not nanometers. A review of Widrow does not indicate any disclosure of nanometer scale components such as nanotubes, nanowires, nanoparticles and the like. Widrow also does not provide, for example, any disclosure or teaching of nanometer-scale manufacturing processes, materials and devices. The Examiner has not provided any evidence from Widrow which indicates otherwise.

Additionally, it is important to note that Widrow does not even provide any teaching or disclosure of a neural network. Where is a teaching of a neural network in Widrow? Widrow provides no teaching of a neural network as taught by Applicant's invention. There is no hint or suggestion of neural network components

such as synapses, neurons and so forth. The "logic memory" taught by Widrow provides no indication of a neural network and in particular, no teaching of a physical neural network as taught by Applicant's invention.

In order to function as a neural network, the device of Widrow must have certain components inherent to a neural network, such as synapses, neurons and so forth. Applicant's specification at paragraphs [009-0014] generally describes some of the features of a neural network and the problems with hardware versus software implementations of neural networks:

Neural networks that have been developed to date are largely software-based. A true neural network (e.g., the human brain) is massively parallel (and therefore very fast computationally) and very adaptable. For example, half of a human brain can suffer a lesion early in its development and not seriously affect its performance. Software simulations are slow because during the learning phase a standard computer must serially calculate connection strengths. When the networks get larger (and therefore more powerful and useful), the computational time becomes enormous.

For example, networks with 10,000 connections can easily overwhelm a computer. In comparison, the human brain has about 100 billion neurons, each of which can be connected to about 5,000 other neurons. On the other hand, if a network is trained to perform a specific task, perhaps taking many days or months to train, the final useful result can be built or "downloaded" onto a piece of hardware and also mass-produced. Because most problems requiring complex pattern recognition are highly specific, networks are task-specific. Thus, users usually provide their own, task-specific training data.

A number of software simulations of neural networks have been developed. Because software simulations are performed on conventional sequential computers, however, they do not take advantage of the inherent parallelism of neural network architectures. Consequently, they are relatively slow. One frequently used measurement of the speed of a neural network processor is the number of interconnections it can perform per second.

For example, the fastest software simulations available can perform up to approximately 18 million interconnects per second. Such speeds, however, currently require expensive super computers to achieve. Even so, approximately 18 million interconnects per second is still too slow to perform many classes of pattern classification tasks in real time. These include radar target classifications, sonar target classification, automatic speaker identification, automatic speech recognition, electro-cardiogram analysis, etc.

The implementation of neural network systems has lagged somewhat behind their theoretical potential due to the difficulties in building neural network hardware. This is primarily because of the large numbers of neurons and weighted connections required. The emulation of even of the simplest biological nervous systems would require neurons and connections numbering in the millions and/or billions.

Due to the difficulties in constructing such highly interconnected processors, currently available neural network hardware systems have not approached this level of complexity. Another disadvantage of hardware systems is that they typically are often custom designed and configured to implement one particular neural network architecture and are not easily, if at all, reconfigurable in implementing different architectures. A true physical neural network chip, with the learning abilities and connectivity of a biological network, has not yet been designed and successfully implemented.

Widrow does not teach weighted connections, nor neurons, synapse, nor a device which can emulate a simple biological neural network. Again, the Applicant asks, where and how is a neural network taught by Widrow?

Additionally, the Applicant notes that Widrow could not possibly provide a teaching of strengthening connections via pre- and post-synaptic activity because the device described by Widrow does not modify its resistance via leads 21 and 22 but rather lead 18. The examiners comparison of leads 21 and 22 to a pre-and post-synaptic electrode are incorrect because the device also contains an addition electrode, 18, without which the device will not function. How can a synapse, a two-terminal device, contain three electrodes? How can leads 21 and 22 be used to modify the electrical resistance when it is explicitly stated by Widrow that lead 18 is needed to provide the electroplating material needed to affect the resistance? (Widrow, C 4, L 34-55.). If the device disclosed by Widrow cannot function without lead 18 and the applicant's invention does not contain such a lead, it follows that the examiners remarks neglect the fact that the two devices are extraordinarily different in both fabrication and function.

The rejection to claim 18 under 35 U.S.C. 102 based on Widrow fails under the aforementioned prima facie anticipation test. That is, Widrow does not provide

for the disclosure of each and every claim limitation of Applicant's claim 18. The Applicant reminds the Examiner that in order to succeed in a rejection to a claim under 35 U.S.C. 102, the reference utilized as a basis for the rejection must disclose each and every claim limitation of the rejected claim. If even one claim limitation or feature is missing, no matter how minor, the rejection under 35 U.S.C. 102 fails. Such claim limitations are enabled by Applicant's specification. In the present case, Widrow does not provide for the disclosure of the LSM taught by Applicant's claims AND specification. Widrow also does not provide for a disclosure of the physical neural network (e.g. based on nanotechnology) taught by Applicant's claims and specification. That is, Widrow does not provide for a disclosure of a physical neural network formed from neural network connections formed in a dielectric solution.

The Applicant therefore submits that the rejection to claim 18 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 18.

Regarding claim 19, the Examiner argued that Widrow discloses the system of claim 19 (the Examiner indicated to see above objections for correction requirements regarding this dependency; this claim has been treated to be dependent from claim 18 for purposes of this office action) wherein said physical neural network further comprises at least one connection network associated with at least one neuron-like node (the Examiner asserted that it remains inherent for a neural network to comprise a connection network as one can not exist without its respective connections), wherein said at least one connection network comprises a plurality of said nanoconnections, including a plurality of interconnected nanoconductors (citing Widrow, C 1-12, particularly C 4, L 24-73, where it discusses the materials used to achieve electroplating. The Examiner asserted that the reaction occurring at the molecular scale of this system contains particles that are in the order of 10^9 that bond in accordance with the occurring chemical reaction.

The Examiner also argued that it is the nanoconductors within the aforementioned nanoconnections providing the channel for electron movement and thus conducting electricity, specifically, the nanoconductors are the particles producing the conductivity, see C4, L 59-73), wherein each nanoconductor of said plurality of interconnected nanoconductors is strengthened or weakened according to an application of an electric field or frequency thereof (citing Widrow, C 1-12, particularly C 4, L 24-73 where it discusses the physical properties and mechanisms of the novel adaptive memory element; also citing Widrow, C 4, L 49-55, where a frequency is inherent in an alternating current. The Examiner argued that strengthening and weakening corresponds to the amount of deposit on the substrate, as more or less will strengthen or weaken the nanoconnections thereof).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 18 apply equally against the rejection to claim 19. Thus, because claim 19 depends from claim 18, and claim 18 has been traversed as indicated above, the Applicant submits that the rejection to claim 19 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 19 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 19.

The Applicant also points out the Examiner's use of the word "reaction" and notes that Applicant's invention does <u>not</u> rely on a <u>chemical</u> process (i.e., a chemical reaction), but rather an <u>electro-mechanical</u> force created by divergent electric fields. The Examiner's comment that the components of the device disclosed by Widrow are particles in the order of 10^-9 neglects the fact that the device in its entirety is on the scale of centimeters. The Applicant respectfully points out that all systems in the known universe are constructed from material at the nanometer, or sub-nanometer scale, but this does not make the systems or devices nano-scale.

Regarding claim 20, the Examiner argued that the Widrow discloses the system of claim 19 wherein: each nanoconductor of said plurality of interconnected nanoconductors experiences an increase in alignment in accordance with an increase or a decrease in said electric field, said frequency, or said combination thereof (arguing that inherently when an electric field is applied to any dipolar particle, such as the nanoconnections described above, it will become aligned accordingly under the physical properties of electricity; also C 4, L 49-55, where a frequency is inherent in an alternating current); wherein nanoconductors of said plurality of interconnected nanoconductors that are utilized most frequently by said at least one neuron-like node become stronger with each use thereof (citing Widrow, C 1-12, particularly C 4, L 24-73 where it discusses the physical properties and mechanisms of the novel adaptive memory element; also C 4, L 49-55, where a frequency is inherent in an alternating current. The Examiner argued that strengthening corresponds to an increase in the amount of deposit on the substrate, assuming using the proper electrolyte described herein - that is, adding the phenol sylphonic acid and Dacolite); and wherein nanoconductors of said plurality of interconnected nanoconductors that are utilized least frequently become increasingly weak and eventually become unaligned (C 1-12, particularly C 4, L 24-73 where it discusses the physical properties and mechanisms of the novel adaptive memory element; also C 4, L 49-55, where a frequency is inherent in an alternating current. The Examiner asserted that less deposit on the substrate will weaken the nanoconnections thereof, increasing resistivity and reducing conductance, thus eventually causing the nanoconductors to become unaligned, corresponding to the dynamic fading memory mechanism).

The Applicant respectfully disagrees with this assessment and notes that the arguments presented above against the rejection to claim 18 apply equally against the rejection to claim 20. Thus, because claim 20 depends from claim 18, and claim 18 has been traversed as indicated above, the Applicant submits that the

rejection to claim 20 is also traversed. Based on the foregoing, the Applicant submits that the rejection to claim 20 has been traversed. The Applicant respectfully requests withdrawal of the aforementioned rejection to claim 20.

IV. Conclusion

In view of the foregoing discussion, the Applicant has responded to each and every rejection of the Official Action. The Applicant has clarified the structural distinctions of the present invention. Applicant respectfully requests the withdrawal of the rejections under 35 U.S.C. §102 based on the preceding remarks. Reconsideration and allowance of Applicant's application is also respectfully solicited.

Should there be any outstanding matters that need to be resolved, the Examiner is respectfully requested to contact the undersigned representative to conduct an interview in an effort to expedite prosecution in connection with the present application.

Respectfully submitted,

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